3D-OOCS: Learning Prostate Segmentation with Inductive Bias

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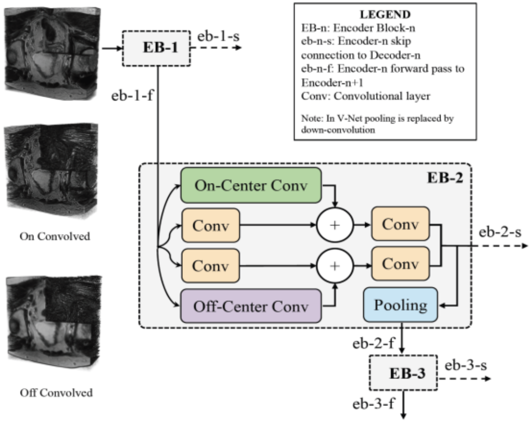
I) Main Motivation

- Current convolutional neural networks (CNN) are not robust in 3D medical image tasks such as prostate segmentation.
- To overcome this, two residual components are added to the second encoder blocks of different 3D U-Net variants.
- The two pathways: on and off center-surround (OOCS), generalise the ganglion pathways in the retina to a 3D setting.
- The OOCS complements the CNN network with sharp edge-detection inductive biases.



II) 3D On-Off Center-Surround Kernels

- The OOCS receptive fields are computed with a difference of two Gaussian functions.

$$DoG_{\sigma,\gamma}(x,y,z) = \frac{A_c}{\gamma^3}\, e^{-\frac{x^2+y^2+z^2}{2\gamma^2\sigma^2}} - A_s\, e^{-\frac{x^2+y^2+z^2}{2\sigma^2}}$$

- γ is the ratio of the radius of the center to the surround, σ is the variance of the Gaussian function, A_c and A_s are the center and surround coefficients respectively.
- We compute the On-and-Off kernels from the same equation, with inverted signs while ensuring that the absolute sum of the negative and positive weights (given by c) are equal.
- The kernel size (k) depends on the radius of the central sphere (r) and γ. For $k = 3$: $r = 1$ and $\gamma = ½$, whereas, for $k = 5$: $r = 2$ and $\gamma = ⅔$.
- For a given input X, we calculate the On and Off responses by convolving X with the computed On-and-Off kernels separately:

$$\chi_{\mathrm{On}}[x,y,z] = (\chi * +DoG[r,\gamma,c])[x,y,z]$$
$$\chi_{\mathrm{Off}}[x,y,z] = (\chi * -DoG[r,\gamma,c])[x,y,z]$$

III) Prostate Segmentation Experiments

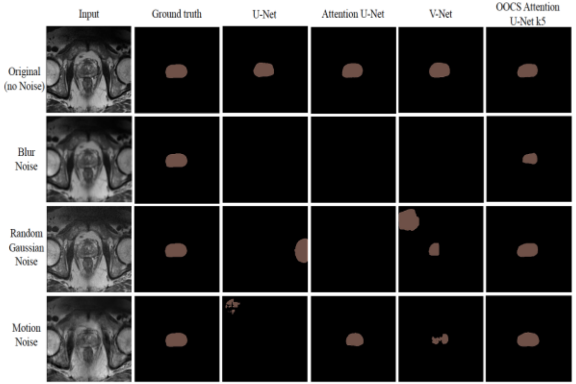
- The prostate MR volumes used in the experiments were obtained from the Medical Segmentation Decathlon (MSD) challenge.
- State-of-the-art (SOTA) base models: UNet, V-Net and Attention-Unet.
- SOTA architectures were extended with OOCS-kernels of different size (k=3 and k=5), then and compared with their respective original models.

Model Name	DSC*	HSD+(mm)
U-Net	0.744 ± 0.24	33.777 ± 37.81
OOCS U-Net (k3)	0.798 ± 0.11	24.518 ± 12.46
OOCS U-Net (k5)	$\mathbf{0.824 \pm 0.07}$	$\mathbf{24.474 \pm 12.48}$
V-Net	0.792 ± 0.16	25.170 ± 22.91
OOCS V-Net (k3)	0.791 ± 0.13	26.488 ± 17.68
OOCS V-Net (k5)	$\mathbf{0.825 \pm 0.08}$	$\mathbf{21.471 \pm 10.01}$
Attention U-Net	0.824 ± 0.09	27.822 ± 14.64
OOCS Att. U-Net (k3)	$\mathbf{0.845 \pm 0.07}$	24.106 ± 14.70
OOCS Att. U-Net (k5)	0.835 ± 0.11	$\mathbf{23.531 \pm 14.89}$

* - Sørensen–Dice coefficient, + - Hausdorff Distance

IV) Robustness Evaluation

- To examine the robustness of the models, we introduced three types of noise: Gaussian blur, random Gaussian noise, and motion transform.
- The segmentation experiments on the MSD dataset show that the OOCS kernels significantly increase the accuracy of CNNs.
- OOCS-Attention U-Net (k5) performs the best prostate segmentation from MRIs.



V) Conclusions

- We introduced the On-Off center-surround to 3D kernels, and designed OOCS encoder blocks in different U-Nets.
- The OOCS extended networks show notable enhancements in prostate segmentation task, and are also robust against distribution shifts.
- Future work would be to employ the OOCS U-Nets to segment prostate tumours, and also expand to other modalities such as CT and PET.

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https://github.com/Shrajan/AAAI-2022